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Annex B. Integration Roadmap with Current Models in 2026, AI-Enabled Implementation, and Ten-Year Benefits

This annex defines a practical pathway for integrating the proposed crustal deformation and log-log convergence model with current operational earthquake and volcanic monitoring models in 2026. It also outlines how artificial intelligence can function as a realistic integration accelerator using currently available technology, and it summarizes the benefits that could emerge over the next ten years through continuous development, calibration, and hybrid deployment. [web:262][web:265][web:266][web:283][web:286][file:242]

1. Integration objective in 2026

The proposed model is best integrated as an additional layer within the current forecasting ecosystem rather than as a replacement for operational systems already in use. In 2026, the most realistic architecture is a layered framework in which long-term hazard models continue to support planning, operational earthquake forecasting continues to update short-term probabilities, earthquake early warning continues to protect populations after rupture begins, and the proposed model adds a precursor-based critical-time surveillance layer before rupture. [web:262][web:265][web:266][file:242]

This same logic applies to volcano monitoring, where existing seismic, deformation, gas, and thermal systems remain central, while the proposed framework contributes a multivariable convergence layer that transforms those observables into a normalized precursor index and an evolving estimate of candidate failure time. AI strengthens this integration by automating multimodal data fusion, anomaly filtering, calibration support, and continuous quality control without displacing physics-based interpretation. [web:284][web:287][web:292][file:242]

2. Integration steps for 2026

2.1 Step 1: Establish the shared data layer

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The first step is to align all relevant monitoring streams into a common time-indexed analytical layer. In tectonic settings, this includes GNSS displacement, InSAR products, seismic catalogs, strain or tilt where available, and auxiliary hydrological or environmental signals. In volcanic settings, it includes the same core deformation and seismic signals plus gas, hydrothermal, thermal, and additional surveillance measurements. [web:247][web:250][web:251][web:252][web:255][file:242]

This step is fully realizable with current technology because geodetic, seismic, and volcanic observatories already operate digital pipelines, and AI-assisted data engineering can now be used to synchronize heterogeneous data streams, classify data quality, fill short gaps, and flag incompatible time segments. Reviews of AI in earthquake forecasting emphasize that multimodal integration is one of the most promising areas for practical progress. [web:278][web:283][web:286][web:291]

2.2 Step 2: Convert observables into normalized model components

The second step is to transform raw observables into the four operational components of the model: deformation velocity, deformation acceleration, auxiliary anomaly field, and seismic-catalog precursor field. Each region should define which local indicators best represent each component and then normalize them into bounded scores before aggregation into $I^*(t)$. [file:242]

This step benefits directly from AI because machine-learning pipelines can support automated feature extraction, anomaly ranking, sensor-specific denoising, and adaptive baseline estimation. Importantly, the role of AI here is not to replace the mathematical structure of the model, but to improve the reliability of the inputs that feed it. [web:283][web:286][web:291][file:242]

2.3 Step 3: Couple the model to current short-term forecasting systems

The third step is to connect the normalized precursor index and rolling estimate of $\widehat{t_c}$ to existing operational earthquake forecasting and volcano-monitoring dashboards. In practice, this means that the model should not initially trigger independent public alerts. Instead, it should first function as a supervised decision-support module shown to analysts alongside OEF probability updates, deformation plots, and catalog-based diagnostics. [web:265][web:266][web:271][file:242]

This is realistic in 2026 because observatories already operate dashboard-based analytical workflows, and AI can assist by ranking windows of concern, prioritizing regions with emerging convergence, and surfacing supporting evidence from multiple data streams. Such use aligns with current expert guidance

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that AI should be integrated with geophysical insight rather than deployed as an opaque substitute. [web:286][web:291]

2.4 Step 4: Add AI-assisted quality control and false-positive discrimination

The fourth step is to deploy AI specifically where it is strongest under current operational constraints: noise filtering, multimodal pattern matching, missing-data handling, anomaly scoring, and false-positive discrimination. This is especially useful for distinguishing true rupture preparation from slow-slip episodes, weather-related hydrological noise, sensor instability, or transient isolated anomalies. [web:279][web:286][web:291][file:242]

Current research shows that multimodal fusion and adaptive AI methods can reduce false alarms and improve cross-sensor reliability when heterogeneous signals are combined in a unified framework. In volcano monitoring, recent work has also shown that AI integrated with satellite and ground-based measurements can identify changes in hydrothermal or eruptive systems that are difficult to resolve with a single data stream alone. [web:279][web:284][web:287]

2.5 Step 5: Run prospective shadow-mode validation

The fifth step is prospective shadow-mode deployment. In this phase, the model runs continuously in parallel with existing systems, generates internal convergence outputs, and records hypothetical alerts without affecting public warning protocols. This allows institutions to measure hit rates, lead times, false positives, and regional calibration needs under real operational conditions. [web:265][web:271][file:242]

AI is highly useful in this phase for retrospective labeling assistance, automated error analysis, hyperparameter search under constraints, and post-event pattern comparison across regions. The purpose is to accelerate learning while maintaining scientific discipline and operational caution. [web:283][web:286][web:291]

2.6 Step 6: Transition to supervised operational integration

After sufficient shadow-mode evaluation, the model can transition into supervised operational use as a decision-support signal inside observatory workflows. In this stage, the output may inform analyst attention, scenario escalation, or coordination with civil-protection authorities, while final alert authority remains with expert teams and institutional protocols. [web:266][web:271][file:242]

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This is the most realistic endpoint for 2026 technology: AI-assisted, human-supervised, physics-informed integration inside an operational ecosystem that already includes seismic, geodetic, and civil-protection layers. [web:286][web:291]

3. Realistic AI roles with current technology

AI can already serve as a practical integration enhancer in at least six ways:

- **Multimodal data fusion:** combining seismic, geodetic, satellite, gas, and environmental data into synchronized feature spaces. [web:279][web:283][web:292]
- **Noise filtering and signal enhancement:** improving the quality of GNSS, seismic, and thermal or satellite-derived observables before model fitting. [web:280][web:286]
- **Anomaly detection:** identifying subtle deviations that may deserve inclusion in $X_3(t)$ or in false-positive discrimination logic. [web:284][web:287]
- **Adaptive calibration:** supporting regional tuning of weights, thresholds, and normalization parameters using constrained learning procedures. [web:283][web:286][file:242]
- **Cross-region knowledge transfer:** learning from regions with richer event histories and transferring useful structure to data-scarce areas. [web:283][web:289]
- **Analyst support:** ranking episodes of concern and generating interpretable summaries rather than replacing institutional judgment. [web:286][web:291]

These roles are achievable with currently available technology because the necessary ingredients already exist: streaming digital observatory data, cloud-scale compute, mature machine-learning methods, and growing evidence that multimodal fusion improves forecasting and monitoring performance. [web:279][web:280][web:283][web:286]

4. Ten-year benefits of continuous integration with AI

Over a ten-year horizon, the combined development of the model and AI-enabled integration can produce several major benefits.

First, calibration quality should improve substantially as more prospective cases accumulate. This would make the model more region-specific, reduce threshold uncertainty, and strengthen confidence in the

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interpretation of $\widehat{t_c}$ stabilization under different tectonic and volcanic regimes. [web:283][web:286][file:242]

Second, multimodal observatory infrastructures are likely to become more interoperable, allowing the model to move from isolated regional experiments toward broader comparative deployment. AI-assisted feature harmonization and transfer learning can help bridge differences in instrumentation density, making the model more portable across countries and hazard environments. [web:280][web:283][web:289]

Third, false-positive control should improve meaningfully. As larger labeled archives become available, AI can learn recurrent non-rupture patterns associated with hydrological forcing, slow slip, instrumentation artifacts, or volcanic background fluctuations, thereby improving discrimination without abandoning physical interpretability. [web:279][web:284][web:286]

Fourth, the model can contribute to a genuinely layered warning architecture. In such an architecture, PSHA would remain the planning layer, OEF the official short-term probability layer, the proposed model the precursor-criticality layer, and EEW the immediate response layer. Over time, this integration could make forecasting ecosystems more continuous across timescales rather than fragmented by institutional silos. [web:262][web:265][web:266][file:242]

Fifth, volcanic and multi-hazard applications may expand significantly. The same AI-enhanced multivariable framework can support unrest monitoring for volcanoes, slope failures, glacier instabilities, or other accelerating geophysical systems, especially when satellite data, gas measurements, and seismic monitoring are combined. [web:284][web:287][web:292][file:242]

Sixth, long-term institutional benefit may emerge through better decision support rather than through claims of perfect prediction. Even moderate improvements in episode prioritization, analyst workload reduction, and earlier identification of critical transitions could have substantial value for civil protection, infrastructure operators, and scientific observatories. [web:266][web:271][web:286]

5. Conclusions

A realistic 2026 integration strategy places the proposed model inside the existing forecasting ecosystem as a supervised precursor-analysis layer connected to geodetic, seismic, satellite, and environmental observatories. Current AI technology is already sufficient to enhance this integration through

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multimodal fusion, quality control, adaptive calibration, anomaly discrimination, and analyst support, provided that it remains physics-informed and institutionally supervised. [web:279][web:283][web:286][web:291][file:242]

The ten-year outlook is especially strong when integration is treated as cumulative system-building rather than as a one-step replacement of current models. In that setting, the model can help extend the warning chain backward in time, improve discrimination between true and false convergence, and strengthen coordination between long-term hazard assessment, short-term operational forecasting, and immediate warning systems. [web:262][web:265][web:266][web:279][web:283][file:242]

The most important conclusion is that the path forward is technically feasible now. The enabling technologies already exist; what is needed is disciplined integration, prospective validation, and human-supervised deployment within trusted operational institutions. [web:280][web:286][web:291]

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